On the priming of risk preferences: The role of fear and general affect

Despoina Alempaki, Chris Starmer, Fabio Tufano†

Abstract: Priming is an established tool in psychology for investigating aspects of cognitive processes underlying decision making and is increasingly applied in economics. We report a systematic attempt to test the reproducibility and generalisability of priming effects on risk attitudes in a more diverse population than professionals and students, when priming using either a positive or a negative experience. We further test fear as the causal mechanism underlying countercyclical risk aversion. Across a series of experiments with a total sample of over 1900 participants, we are unable to find any systematic effect of priming on risk preferences. Moreover, our results challenge the role of fear as the mechanism underlying countercyclical risk aversion; we find evidence of an impact of general affect such that the better our participants feel, the more risk they take.

Keywords: priming, risk preferences, replication, emotions, experiment

JEL classification: C91, D81, D91

PsycINFO classification: 2300

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1. Introduction

Over at least three decades, priming research – using subtle cues that unconsciously influence people's behaviour – has become a well-established area of study in social psychology (e.g., Molden, 2014). More recently, the use of priming techniques has started to feature in economics (see Cohn and Maréchal, 2016, for a review) including prominent work demonstrating the apparent malleability of risk preferences (e.g., Benjamin et al., 2010). Indeed, a substantial number of studies in psychology, economics and finance have shown that making negative (positive) experiences mentally salient, via priming, decreases (increases) subsequent risk taking behaviour. For example, Erb et al. (2002) alter risky behaviour of students by asking them to rank the frequency of occurrence, in everyday language, of adjectives with risk-averse or risk-seeking connotations and show that this effect may be quite enduring. Gilad and Kliger (2008) find that the behaviour of both financial professionals and students is affected by priming them using short, risk averse or risk seeking vignettes, although the effect is more pronounced for the professionals. Cohn et al. (2015) show that priming financial professionals to bring to mind a stock market crash significantly decreases their risk taking compared to when primed with a stock market boom.[1] They further investigate the causal mechanism through which priming influences risk preferences and provide evidence for fearful emotions being the channel underlying such "countercyclical" risk aversion (see also Callen et al., 2014; Guiso et al., 2013); as such, this finding contributes to a substantial literature investigating relationships between emotions and risk taking both in economics (e.g., Hirshleifer and Tyler, 2003; Kamstra et al., 2003) and in psychology (e.g., Hockey et al., 2000; Lerner and Keltner, 2000; Loewenstein et al., 2001).[2]

As part of this growing literature, however, some writers have challenged the replicability or generalisability of priming effects.[3] For instance, evidence from cognitive psychology (see Shanks et al., 2013) suggests that unconscious influences of priming techniques may be both modest and very short-lived (less than a second). Recent meta-analyses of priming studies indicate that available evidence may be subject to small-study effects and publication bias (Gomes and McCullough, 2015; Shanks et al., 2015; Vadillo et al., 2016). Furthermore, recent attempts to extend the study of countercyclical risk aversion to other samples has found limited support for priming effects: König-

[1] Further studies that successfully use priming to manipulate risk preferences include Aldrovandi et al., 2017; Hamilton and Biehal, 2005; Harris and Blair, 2006; Kusev et al., 2012; Ludvig et al., 2015; Mandel, 2003. For discussion of the literature on broader dimensions of priming see, for example, Bargh, 2006.

[2] See also Chou et al., 2007; Drichoutis and Nayga, 2013; Fehr et al., 2007; Isen and Geva, 1987; Isen and Patrick, 1983; Williams et al., 2003; Yuen and Lee, 2003 for further studies on the effect of emotions on risk taking.

[3] For example, see volume 32 (Issue Supplement) on "Understanding Priming Effects in Social Psychology" in *Social Cognition* in 2014 or studies in the social priming literature (Doyen et al., 2012; Newell and Shanks, 2014; Newell and Shaw, 2017; Shanks et al., 2013; 2015) reporting little convincing evidence of priming on behaviour.

Kersting and Trautmann (2018) do not find any evidence that the Cohn et al. (2015) priming task influences students; Newell and Shaw (2017) report three experiments with limited or no support for priming effects on students' risk attitudes. This raises potentially interesting questions about, for example, whether people outside of the financial professions (including students) are largely immune to priming effects in this domain, or whether different sorts of priming task might be more effective at stimulating countercyclical risk aversion in other groups.

In this paper, we report results from four experiments involving a total of 1939 participants and designed with three main objectives in mind: first, to test the reproducibility and generalisability of the effect of priming (negative or positive) experiences on subsequent risk taking in a population that is less specialised than professionals and more diverse than students; second, we test the impact of a range of different priming techniques; third, we test the role of fear as the underlying mechanism through which priming affects risk preferences.

We conduct our experiments online using Amazon Mechanical Turk (MTurk). While MTurk samples are not fully representative of the US population as a whole (Paolacci and Chandler, 2014), they offer the attraction of being able to gather large samples to underpin well-powered tests, from subject pools which are more diverse and more representative than the typical student subject pools used in many lab experiments (Berinsky et al., 2012; Buhrmester et al., 2011; Casler et al., 2013; Stewart et al., 2017).[4] Notwithstanding these potential advantages of MTurk, however, there has been considerable debate about potential limitations (e.g., see discussions in Chandler et al., 2015; Hauser et al., 2018). While good scientific practice requires consideration of potential limitations, in our assessment, currently available evidence supports using evidence based on MTurk samples, alongside other sources. Indeed, a variety of studies have shown that the data gathered using MTurk are reliable in the sense of replicating a wide range of behavioural patterns established initially through laboratory investigations with mainly student subject pools (e.g., Amir et al., 2012; Arechar et al., 2018; Buhrmester et al., 2011; Horton et al., 2011; Paolacci et al., 2010; Rand, 2012). The relevant evidence includes a number of studies (e.g., D'Acunto, 2015a, 2015b; Horton et al., 2011; Morris et al., 2013; Preece and Stoddard, 2015; Welsh and Ordóñez, 2014) demonstrating the presence of strong priming effects in experiments with MTurk samples.[5]

[4] For example: Casler et al., 2013 show that MTurk samples are more socio-economically and ethnically diverse than student samples; Buhrmester et al., 2011 show that MTurk participants come from 50 different countries. Compared to the average U.S. population, MTurk samples tend to be younger and better educated, but are more likely to have lower income and be unemployed or underemployed (Levay et al., 2016; Stewart et al., 2017).

[5] Although MTurkers do self-report multitasking (e.g., Chandler et al., 2014) or engaging in distractions (e.g., Clifford and Jerit, 2014) while participating in experiments, they tend to show the standard decision making biases – such as loss aversion, present bias, risk aversion for gains, risk seeking for losses and as noted above, priming effects – with similar effect sizes to traditional samples, even though they may seem to be paying less attention to the experimental materials (e.g., Goodman et al., 2013). However, since all of our studies were conducted online, we cannot rule out the possibility that the observed effect sizes in our studies might be lower due to less control over subjects' attention compared to typical studies conducted in a lab. Further issues, which might have

For our investigations, in Experiment 1 and like König-Kersting and Trautmann (2018) we use the priming technique of Cohn et al. (2015). Subjects are asked to imagine they participate in a stock market crash (boom) and, after answering a series of questions regarding their investment strategy in such a scenario, they self-report their level of fear and general affect. Subsequently, their willingness to take risk is assessed via a standard *investment task* (adapted by Gneezy and Potters, 1997, as in Cohn et al., 2015). We find no effect of priming. However, it is a feature of the results of our Experiment 1 and those of König-Kersting and Trautmann (2018) that both failed to generate any strong emotional reaction among participants. As such, if indeed fear is the driving force of countercyclical risk aversion, it is no surprise that we fail to find such an effect. In light of these results, we conducted three further experiments in which we modified the priming task with the aim of inducing stronger fear responses. Specifically, we adapted Cohn's et al. (2015) priming questions aiming to make them more relevant for our more diverse population; we also borrowed and adapted other established priming techniques from previous literature (e.g., Erb et al., 2002; Gilad and Kliger, 2008; MacDonald et al., 2012).

To pre-empt our results, after running four different experiments involving over 1900 participants (with at least 143 subjects per experimental treatment), we found no evidence that priming significantly influenced risk preferences. We suggest several possible interpretations. First, the original (treatment) effect reported in Cohn et al. (2015) could be a false positive (i.e., a Type I error). Second, the original effect of Cohn et al. (2015) could be an overestimate of the true effect size (see Camerer et al., 2018, for a discussion of inflated true positives) and, if so, our studies could be underpowered to detect the smaller true effect.[6] Third, since we run our experiments with a subject pool different from the original one, our results may be indicative of a boundary condition for the effect reported in Cohn et al. (2015): that is, the effect may not generalise from financial professionals to the population represented in MTurk. Differences in behaviour between professionals and non-professionals have been widely documented in the literature (e.g., see reviews by Ball and Cech, 1996; Fréchette, 2015),[7] and it might be the case that possessing a professional investor's identity is necessary for priming past experiences to be effective in stimulating countercyclical risk aversion. Crucially, however, our failure to find a priming effect holds independently of whether or not we successfully manipulated emotions. We are able to reject the premise that, in our environment, fear drives risk averse behaviour; if anything,

undermined priming effects in our studies relate to concerns about non-human workers (i.e., bots) completing tasks in online studies (e.g., Crump et al. 2013; Mason and Suri 2012) or excessively experienced MTurk participants (when compared to subjects in laboratory studies) who might have been familiar with our experimental paradigm (e.g., Rand et al., 2014; Rand, 2018).

[6] Our studies have high statistical power to detect an effect in the same direction and of the same size as the original Cohn et al.'s (2015) effect. More specifically, the total sample size required to detect the effect size (Cohen's d=0.421 for the risky investment task) reported by Cohn et al. (2015) with power at least 95% in a one-sided t-test of independent groups is N=246 (and for a two-sided test is N=296). All calculations were implemented using software GPower 3.1 (Faul et al., 2009).

[7] The evidence from the literature is mixed: some studies find that professionals are less prone to decision biases (e.g., Alevy et al., 2007), some find no behavioural differences (e.g., Bolton et al., 2012), whereas others suggest that professionals are more affected than non-professionals (e.g., Haigh and List, 2005; Gilad and Kliger, 2008).

our data suggest that general affect is the channel through which emotions affect risk preferences, since we find that in all of our experiments where general affect was significantly influenced by priming, it is positively correlated with risk taking: the better our participants feel, the more risk they take (in line with e.g., Chou et al., 2007; Nguyen and Noussair, 2014; Williams et al., 2003; Yuen and Lee, 2003).

The paper is organized as follows. Section 2 reviews key features of our setup and results of Experiment 1. Section 3 summarizes the main aspects and findings from our three additional experiments aimed at successfully manipulating participants' emotions. Section 4 presents aggregate results from a composite analysis and Section 5 concludes.

2. Experiment 1

2.1 Experimental Design

Experiment 1 is designed to implement the priming manipulation of Cohn et al. (2015) in an MTurk population.[8] Subjects were asked a few introductory questions regarding investing behaviour before proceeding to the priming part. In the priming part, subjects were first exposed to a hypothetical stock market scenario. For this, subjects were shown a diagrammatic representation of a stock market history and its projected future (based on the one used by Cohn et al., 2015) but randomly assigned to either the positive or the negative treatments which differed in the direction of the market trend (Figure 1 – Panel A and B depict scenarios with positive and negative stock market trends, respectively).

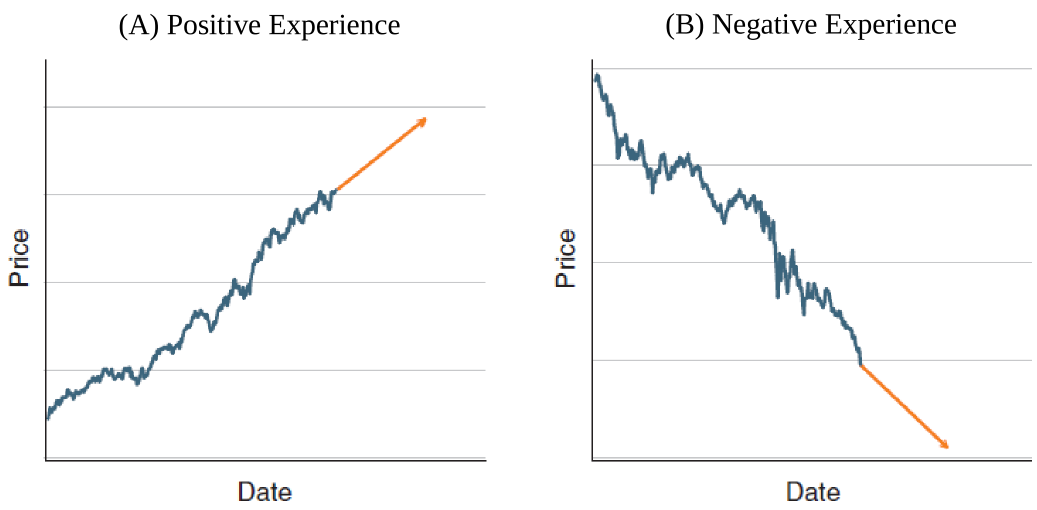


Figure 1. Stock market hypothetical scenarios.
Note: Panel A (B) was used in the positive (negative) treatment and depicts a scenario with a positive (negative) stock market experience. Adapted from Figure 1 in Cohn et al. (2015).

Participants were asked to imagine that they had some investments in the stock market and they were experiencing a continuing market boom (or crash). They were told they expected the positive

[8] Full instructions for Experiment 1 are reported in Appendix A.

(negative) development to continue as indicated by the arrow in Figure 1A (1B). Subjects were subsequently asked a series of questions about what their investment strategy would be had they experienced such a situation (for example, “Would you sell/buy individual stocks? Explain briefly why”). We used four out of the five priming questions from Cohn et al. (2015) (We removed the question “Would you invest in Exchange Traded Funds? Explain briefly why” on grounds that it would not have been meaningful for our sample of non-professional investors). After finishing the priming part, participants were asked to self-report their general affective state by selecting one out of nine manikins (Bradley and Lang, 1994) and to self-report their level of fear on a seven-point Likert scale (Bosman and van Winden, 2002) (see Appendix A for details).

Subsequently, participants made two investment decisions, one of which was randomly selected (after both decisions) for payment. More specifically, they were given a (notional) $200 and had to decide how much of it to invest in a risky asset. The amount not invested was theirs to keep. In order to illustrate the probabilities of the investment being successful, subjects saw a picture of a plastic box containing yellow, red and blue balls and were told that in the good scenario (indicated by a yellow ball) they would get 2.5 times the amount invested. In the bad scenario (indicated by a red or blue ball), they would lose their invested amount. Two variants of the investment task were used: one under risk, where subjects could infer the exact probability of success (50%, as per Figure 2 Panel A), and one under ambiguity, where subjects could not infer the exact probability of success (that was set by us again to 50%, Figure 2 Panel B). Subjects in the ambiguity task were asked to guess the share of yellow balls as a measurement of their expectations. As in Cohn et al. (2015), the ambiguity task was introduced before the risk task to avoid anchoring participants to the 50% probability (Tversky and Kahneman, 1974).

(A) Risk (B) Ambiguity

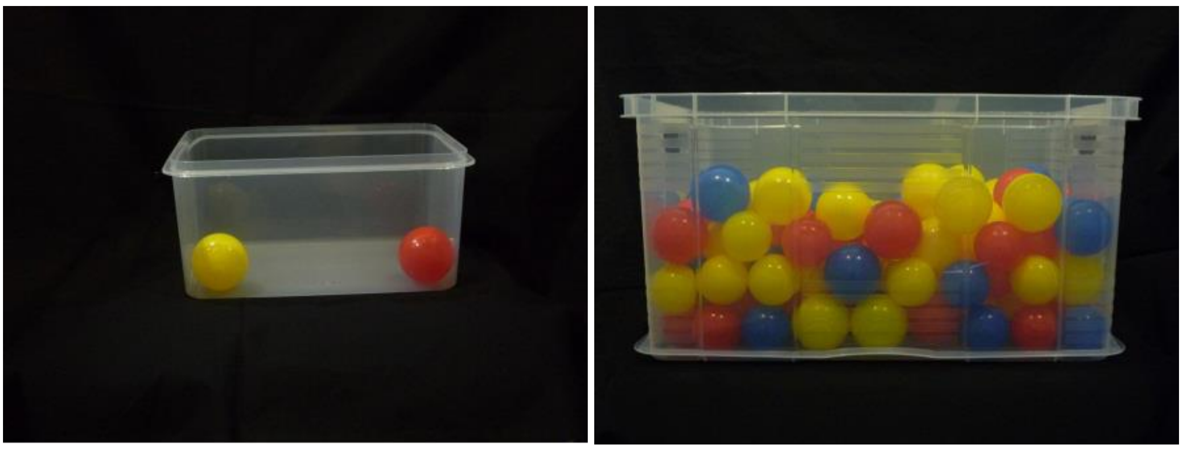


Figure 2. Pictures of plastic boxes to illustrate probabilities.
Note: Panel A (B) was used in the risk (ambiguity) variant. Adapted from Figure A2 in Cohn et al. (2015).

The final part of the experiment included two survey questions used by Cohn et al. (2015) to serve as alternative measurements of expectations (i.e., assessing participants' general optimism (Scheier et al., 1994), and the likelihood of losing their job in the near future). Finally, as a second measurement of their market experience, subjects were asked whether they had previously participated in the stock market. The experiment concluded with a short questionnaire eliciting sociodemographic characteristics.[9]

2.2 Procedures

We conducted Experiment 1 online with subjects recruited on MTurk. Ethics approval was obtained from the [*Institution Name removed in accordance to double-blind review policy*] Research Ethics Committee. A total of 294 participants completed the experiment (average age=35 years; and 53% male).[10] They received a flat fee of $0.50 for participating, plus an additional payment ranging from $0 to $5 depending on their choices and chance.[11] Participants received instructions and made their decisions via web browsers and were paid via MTurk.[12] After deciding to participate, subjects were directed to the experimental tasks on an external webpage. The tasks were coded using Qualtrics (http://www.qualtrics.com/).

[9] We did not include the financial literacy test judging it non-suitable for our more general population sample.

[10] In Appendix C, we report randomization checks for gender, age and market experience across experiments (Table C4) and across treatments for a given experiment (Table C5). We cannot reject the null hypothesis that our variables are balanced across treatments and experiments (5% significance level) in 15 out of 18 comparisons. We find that the distribution of participants having invested money in the stock market is significantly different across experiments (ranging from 59% to 70%, chi-square p-value=0.005), that age is significantly different across experiments (ranging from 35.4 to 38.5 years, Kruskal-Wallis p-value=0.001) and that in E2-W2 more participants have invested money in the stock market in the negative compared to the positive treatment (75% vs 65%, chi-square p-value=0.041). We control for gender, age and market experience in all of our regressions.

[11] Participants were instructed that their earnings from the investment task would be exchanged at a 1:100 rate in Experiment 1. In the original Cohn et al. (2015) experiment, participants received an endowment of 200 CHF and the payment was implemented for real for 1 every 5 participants. Our incentive scheme deviates from the original study, since we adjust our incentives to an MTurk population where the average pay is $1.39 per hour (see D'Acunto, 2015a). Although we cannot rule out that the different incentives might be a hidden moderator of the priming (i.e., priming effects could show up only if stakes are much higher), we think that this is unlikely. König-Kersting and Trautmann (2018) endow their student sample in the lab with 25 euros each and similar to Cohn et al. (2015) implement the payment scheme for 1 out of 5 participants; they do not find any significant effect in the investment decisions. Furthermore, there is evidence from MTurk studies that use priming techniques in other contexts and successfully influence subsequent risk taking using lower incentives (e.g., D'Acunto (2015a) that primes male identity or D'Acunto (2015b) that manipulates exposure to anti-market rhetoric).

[12] Participants receive a completion code upon finishing the experiment, and then return to MTurk where they input the completion code in order to be compensated for their effort. All participants who input the completion code are included in the analysis.

2.3 Results for Experiment 1

Figure 3 depicts the average investment shares in the two variants of the investment task.

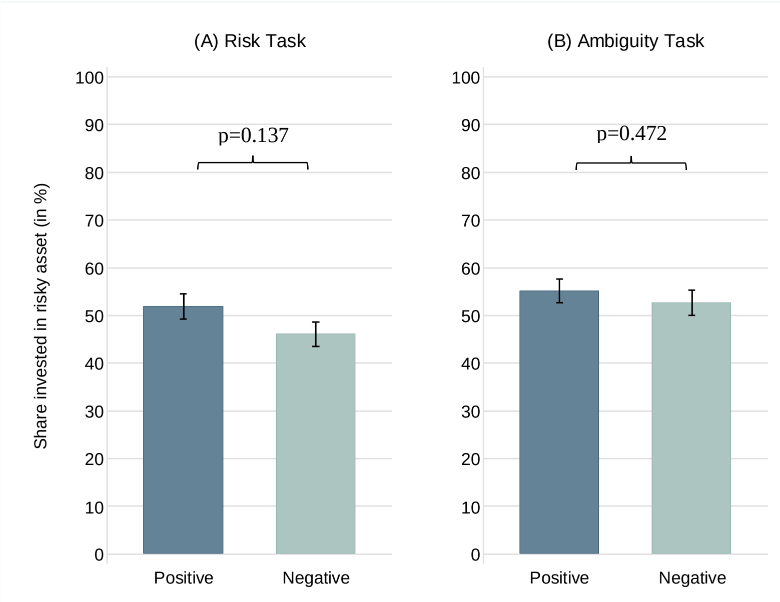


Figure 3. Average investment decisions in Experiment 1.
Notes: The figure shows average investments in the risk task (panel A), and the ambiguity task (panel B), by treatments. Error bars indicate standard errors of the mean.

In the risk variant of the investment task, on average, participants invested 52% of their endowment in the positive treatment and 46% in the negative treatment. Although this difference is in the same direction as in the Cohn et al. (2015) study, it is not statistically significant (Wilcoxon rank-sum p-value=0.137, z=1.489). There is no statistically significant difference in the ambiguity task either, where subjects invest 55% and 53% (Wilcoxon rank-sum p-value=0.472, z=0.720) of their endowment in the positive and negative treatments respectively.

Following the approach of Cohn et al. (2015), we use OLS regressions to control for individual differences in socio-demographic characteristics and market experience. The models we estimate are:

$$y_{ik} = \beta_0 + \beta_1 Negative_i + \beta_2 Ambiguity + \beta_3 X_i + \varepsilon_{ik} \qquad (1)$$

$$y_{ik} = \beta_0 + \beta_1 Negative_i + \beta_2 Ambiguity + \beta_3 Negative_i \times Ambiguity + \beta_4 X_i + \varepsilon_{ik} \qquad (2)$$

The dependent variable, y_{ik}, represents the percentage share of the endowment that participant *i* invested in task *k*. *Ambiguity* is a dummy for the ambiguity task and *Negative* is a dummy for the negative prime treatment. X_i contains the controls for participants' *Age*, *Gender*, and *Market experience*.[13] The results from the OLS regressions are depicted in Table 1.

[13] In E1 we asked participants' two questions related to their market experience. The first asks "How often, if at all, do you deal with investment instruments (purchase and sale)?", and the second asks "Have you ever invested

	Share invested in the risky asset	
	(1)	(2)
Negative	-4.855 (3.376)	-6.529 (3.676)
Ambiguity	4.920*** (1.424)	3.291 (2.083)
Negative × Ambiguity		3.349 (2.837)
Age	-0.225 (0.136)	-0.225 (0.136)
Male	6.277 (3.342)	6.277 (3.345)
Market Experience	-0.325 (3.691)	-0.325 (3.694)
Constant	56.235*** (5.962)	57.050*** (5.980)
N	588	588
Clusters	294	294
R^2	0.028	0.029

Table 1. Regression analysis of investment decisions for Experiment 1.

Notes: We report OLS coefficient estimates (standard errors clustered on individuals). The dependent variable is the share invested as a percentage of the endowment. “Negative” is a dummy for the negative prime treatment and “Ambiguity” is a dummy for the ambiguity task. The interaction term “Negative × Ambiguity” allows the treatment effect to be different in the risk and ambiguity variants. “Age” is in years, and “Male” is a gender dummy. “Market Experience” is a dummy for individuals who report having invested money in the stock market. ***p<0.01, **p<0.05.

Column (1) reveals that the coefficient for the negative prime dummy is negative, consistent with participants investing less in the negative compared to the positive prime treatment. However, this result is not statistically significant (p=0.151, t-test). When allowing for the negative prime treatment effect to vary across tasks (Column (2)), we find that the negative correlation between the treatment effect and the risk variant of the task, though increased, remains insignificant (p=0.077, t-test).

We also test whether our treatment manipulation had any influence on expectations relative to the ambiguity task. Similar to Cohn et al. (2015), we use two proxies for expectations: the guessed probability of success in the investment task and a self-reported measure of optimism.[14] Results are reported in Table 2 and, in line with Cohn et al. (2015) and König-Kersting and Trautmann (2018), we find no effect of priming on expectations.

money in the stock market?”. Since our subject pool is not confined to investors, departing from Cohn et al. (2015), we include the second question as a control variable. (In Experiments 2-4 we only asked participants this second question, viewing the first as less suitable for non-professionals). The treatment effects in E1 remain insignificant using the answers in the first question as a control variable instead (see Appendix C).

[14] Our conclusion that the priming did not influence expectations also holds if we use the degree of agreement with the statement “It is unlikely that I will lose my job in the next six months” as an alternative measure.

	Guessed probability of success	General optimism
	(1)	(2)
Negative	1.626	0.231
	(1.624)	(0.181)
Age	0.082	0.020***
	(0.073)	(0.008)
Male	-3.619**	0.238
	(1.631)	(0.178)
Market Experience	0.473	0.680***
	(1.834)	(0.210)
Constant	48.046***	2.521***
	(2.887)	(0.342)
N	294	294
R^2	0.026	0.086

Table 2. Regression analysis of expectations in Experiment 1.
Notes: We report OLS coefficient estimates (robust standard errors in parentheses). The dependent variables are: in Column 1, the percentage of winning balls in the ambiguity task and in Column 2, the degree of agreement with the statement "Overall, I expect more good things to happen to me than bad". The remaining variables are as defined above in the Table 1 notes. *** p<0.01, ** p<0.05.

In Cohn et al. (2015), the key identified channel affecting risk taking is emotions and, more specifically, *Fear*. We now focus on emotions to see how they were affected by our priming manipulation. The results are depicted in Figure 4.

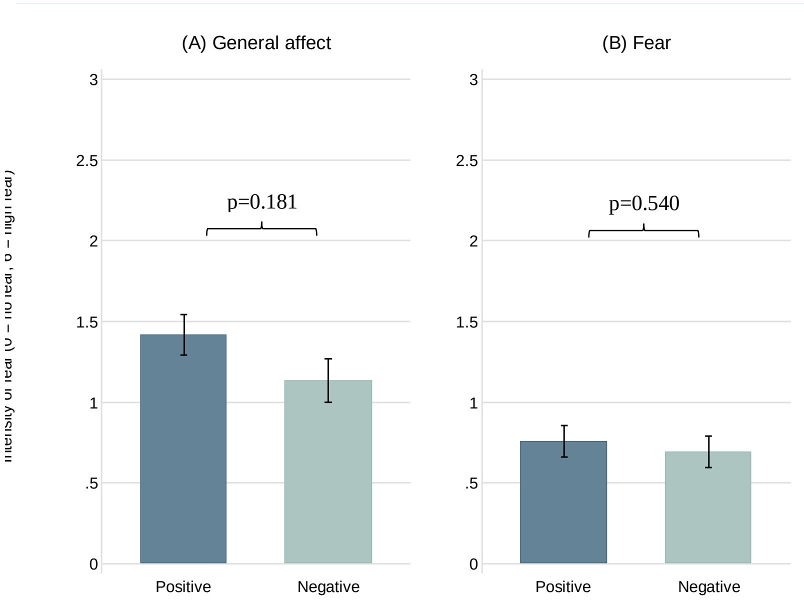


Figure 4. Priming and emotions (Experiment 1)
Note: This figure presents averages in subjects' general affect (panel A) and fear (panel B) in the positive and negative priming treatments. Error bars indicate standard errors of the mean.

As we can observe in Figure 4, subjects report that they feel generally less good on average after a negative experience, although not significantly so (Wilcoxon rank-sum p-value=0.181, z=1.337). The average level of fear is slightly lower after a negative experience, but far from reaching significance

(Wilcoxon rank-sum p-value=0.540, z=0.613). Table 3 reports the results from OLS regressions investigating relationships between risk taking, priming and reported emotions.[15]

	General affect	**Fear**	**Share invested in risky asset**			
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Negative	-0.262	-0.089			-4.570	-4.960
	(0.180)	(0.139)			(3.373)	(3.371)
Ambiguity			4.920***	4.920***	4.920***	4.920***
			(1.424)	(1.424)	(1.425)	(1.425)
General affect			1.214		1.088	
			(1.076)		(1.082)	
Fear				-1.098		-1.177
				(1.442)		(1.456)
Age	0.000	-0.014**	-0.206	-0.219	-0.226	-0.241
	(0.008)	(0.006)	(0.136)	(0.138)	(0.135)	(0.136)
Male	-0.056	-0.285**	6.243	5.852	6.338	5.942
	(0.182)	(0.144)	(3.349)	(3.388)	(3.334)	(3.373)
Market Experience	0.829***	-0.071	-1.308	-0.378	-1.227	-0.408
	(0.213)	(0.158)	(3.736)	(3.668)	(3.741)	(3.674)
Constant	0.871***	1.448***	52.306***	54.690***	55.288***	57.941***
	(0.313)	(0.267)	(5.640)	(5.851)	(5.996)	(6.157)
N	294	294	588	588	588	588
Clusters			294	294	294	294
R^2	0.068	0.034	0.026	0.024	0.031	0.030

Table 3. Regression analysis of emotions (Experiment 1).

Notes: We report OLS coefficient estimates (robust standard errors for Columns 1 and 2, clustered at the individual level for Columns 3-6). The dependent variables are: in Column 1 the level of general affect (from -4: negative to 4: positive), in Column 2 the level of fear (from 0: no fear to 6: high levels of fear), in columns 3-6 the share invested as a percentage of the endowment. The remaining variables are as defined above in the Table 1 notes. *** p<0.01, ** p<0.05.

From Table 3, it can be seen that we find no effect of positive or negative priming on either the level of reported general affect (see model (1)) or the reported level of fear (see model (2)). In models (3) to (6) the dependent variable is the level of risk taking. Across these models, we find no significant effect of priming and no significant effect of either emotion. Hence, the null effects reported by König-Kersting and Trautmann (2018) appear to extend to a more diverse population than students. One possible, perhaps plausible, interpretation of these results is that we find no treatment effect of the prime on risk taking behaviour *because* it has failed to trigger the fear response which Cohn et al. (2015) identify as the channel through which negative priming reduces risk taking. To test this interpretation, in Section 3, we present a set of further experiments which use modified priming tasks adjusted in the hope of generating a significant shift in fear responses in an MTurk population.

[15] Following Cohn et al.'s (2015) and König-Kersting and Trautmann's (2018) analyses, we test the effect of fear and general affect separately. Our results do not change if we control for them simultaneously (see Appendix C).

3. Experiments 2-4

3.1 Design

In this section, we report a series of new experiments conducted using broadly the same procedures as Experiment 1 but with adjustments designed to shed light on two key issues. The first is whether we could design adjusted priming tasks – for positive and negative experiences of risk – that would impact emotional responses of an MTurk population and, in particular, those for fear. The second issue is whether our adjusted priming tasks impact risk taking behaviour and if so, whether variation in risk taking is associated with emotional reports (especially fear).

We report three new experiments which we label E2, E3 and E4. Details of key features of these experiments are provided in Table 4. Note that we collected two waves of data for Experiment 2 (labelled E2-W1 and E2-W2 below).[16] The main differences across experiments E2-E4 relate to the ways in which we implemented priming. The key guiding objective was to vary aspects of the priming tasks with a view to influencing emotional responses. Conditional on successfully manipulating emotions with one or more of the priming tasks, we could thereby test whether subsequent risk taking would be impacted by them. We summarise key features of the priming tasks for each experiment in the second column of Table 4, and comment further on these manipulations here.

Consider first Experiment E2, the details of which are summarised at the top of Table 4. In E2, we continued to base the priming task on the hypothetical stock market scenario used in Cohn et al. (2015), König-Kersting and Trautmann (2018) and in our Experiment 1. The key change was the use of questions designed to be more meaningful for individuals who did not have significant investment experience. The text in the 'priming' column of Table 4 for Experiment E2 illustrates an example of an additional question, where subjects were asked to consider how variation in stock performance might affect them personally (instead of considering whether they would purchase real estate).[17] We conjectured that such questions might render consideration of hypothetical stock market performance (via the positive or negative graphs) more relevant to our subjects, given the typical personal experience of our subject pool.

For Experiments E3 and E4, we moved away from the style of priming task used in Experiment 1 and instead adopted different styles of priming task, adapting established approaches used elsewhere in the priming literature (e.g., Erb et al., 2002; Gilad and Kliger, 2008; MacDonald et al., 2012), with a view to creating positive and negative associations with risk. The rationale behind moving away from a hypothetical stock market scenario was that priming via such a task might not be adequate to produce

[16] The reason is that in the first wave we found that participants increased their risk taking after been exposed to the negative prime when controlling for the level of general affect (see Table 8). To test the robustness of this effect, we decided to replicate E2.

[17] Full instructions of Experiments 2-4 are reported in Appendix B.

a strong emotional response among a population who have not, typically, participated frequently in a stock market. With this in mind, we followed two alternative routes. In Experiment E3, we asked participants to describe a risk-related situation from their own past using either the positive or negative variant of the instruction presented in the middle row of Table 4.[18] Our conjecture was that asking participants to draw on personal experience might be more effective at generating an emotional response associated with risk, than the prime used in Experiment 1 which might not be related sufficiently well to our typical participant's own experience. For Experiment E4, participants were presented with vignettes associating risk with either prudence and loss for the negative prime or excitement and gain for the positive prime (see bottom row of Table 4). Subsequently, participants were asked to read their vignette and memorise as many adjectives as they could, knowing that they would be asked to recall them afterwards. Existing research suggests that such tasks can be effective priming techniques and that requiring memorisation may prolong the duration of priming effects (see for example Erb et al., 2002; Henson and Rugg, 2003; MacDonald et al., 2012).

We kept the investment task constant across all our experiments; besides allowing us to compare behaviour across all experiments, the task has the attraction of capturing whether any change in risk behaviour is taking place through the channel of preferences or expectations.[19] It also allows us to combine both risk and uncertainty measurements, which may be important as uncertainty is often a salient characteristic of real financial situations.[20]

[18] Similar techniques have been used for example by Callen et al. (2014) and Lerner et al. (2003).

[19] Similar to Cohn et al. (2015), König-Kersting and Trautmann (2018) and E1, subjects in the ambiguity task were asked to guess the share of yellow balls. This allows us to test whether changes in risk taking are driven by changes in risk preferences or changes in beliefs (i.e., the priming manipulation might have affected subjects' assessments of the likelihoods of the good or bad states).

[20] In E3-E4, we refer to the "risky asset" as "risky account" and to the "investment decisions" as "decisions", since our priming is not related to the stock market.

<table>
<tr><th colspan="2">Experiment</th><th>Priming technique</th><th>N</th><th>Male</th><th>Age</th><th>Payment</th></tr>
<tr><td rowspan="2">Experiment 2 (E2)</td><td>Wave 1 (W1)</td><td rowspan="2">Similar to Experiment 1, but with more questions that were adjusted to non-professional investors. For example, we substituted the question “Would you consider purchasing real estate (for instance a house)? Explain briefly why.” with the question “Please list the different ways in which your life would be affected by the stock market crash (boom).”</td><td>391</td><td>51%</td><td>37</td><td>Flat fee of $0.50 plus bonus ($0-$5)</td></tr>
<tr><td>Wave 2 (W2)</td><td>402</td><td>49%</td><td>39</td><td>Flat fee of $0.50 plus bonus ($0-$5)</td></tr>
<tr><td colspan="2">Experiment 3 (E3)</td><td>Answer the question “Describe a negative (positive) experience you had involving losing (winning) money. This could be anything, for example losing (winning) money from investing, from gambling, from a lottery ticket or from any other situation that resulted in a financial loss (gain) for you”.</td><td>451</td><td>48%</td><td>36</td><td>Flat fee of $0.50 plus bonus ($0-$1)</td></tr>
<tr><td colspan="2">Experiment 4 (E4)</td><td>“Read a story and memorize as many adjectives as possible”. The adjectives are taken from a story describing either a positive or negative experience such as to advocate risk averse and risk seeking behaviour (e.g., responsible versus adventurous, loss versus gain).</td><td>401</td><td>45%</td><td>37</td><td>Flat fee of $0.50 plus bonus ($0-$5)</td></tr>
</table>

Table 4. Details of Experiments 2-4.[21]
Note: In E2-W1, we elicited subjects’ socio-demographics at the beginning of the experiment.

3.2 Results for Experiments 2-4

We first examine whether our priming manipulations were successful in triggering emotions. The average levels of general affect and fear are depicted in Figure 5. We organize the results such that each row of the figure corresponds to the same emotion and each column corresponds to the same experiment. Eyeballing Figure 5, we can see that emotions were successfully altered in the same direction as in Cohn et al. (2015) for 3 out of 4 experiments (all Wilcoxon rank-sum p-values<0.001 for E2-W1, E2-W2 and E3). A negative prime leads to participants reporting lower levels of general affect and higher levels of fear. These results are confirmed by OLS regressions, reported in Table 5, where we observe that, with the exception of Experiment 4, negative primes are associated with highly significant increases in fear and reductions in general affect.

[21] In some of our experiments, we included further treatments that examine different research questions, i.e., they either involve no priming or they examine whether the degree of social connectedness to an experience affects risk taking. Experiment E2-W1 was conducted in three sessions for the negative treatment and in one session for the positive treatment. Experiments E1, E2-W2, E3 and E4 were respectively conducted in one session.

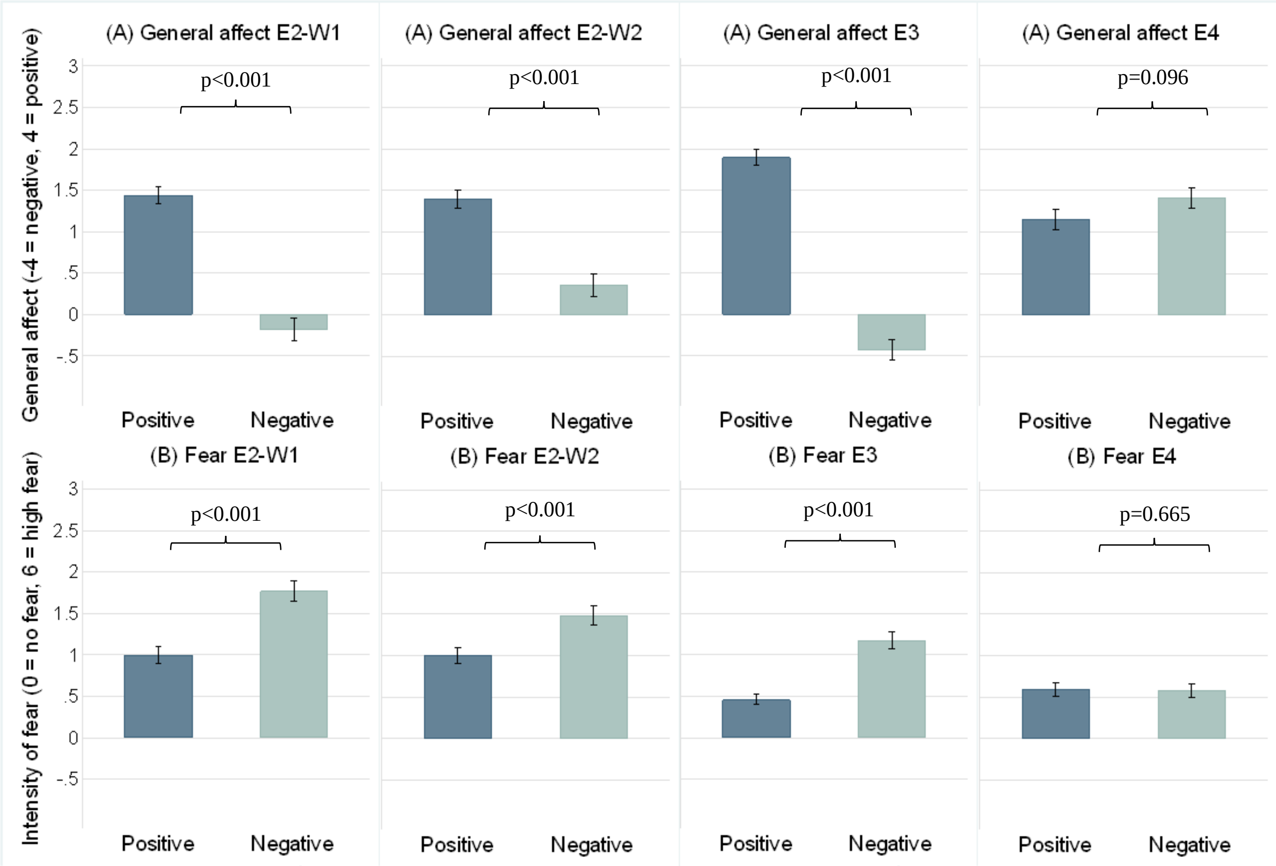


Figure 5. Priming and emotions (Experiments 2-4).

Notes: This figure presents averages in subjects' general affect (ranging from "-4=negative" to "4=positive" – panel A) and fear (ranging from "0=no fear to 6=high fear" – panel B) in the positive and negative priming treatments for all new experiments. Error bars indicate standard errors of the mean.

	E2-W1		E2-W2		E3		E4	
	General affect (1)	**Fear (2)**	**General affect (1)**	**Fear (2)**	**General affect (1)**	**Fear (2)**	**General affect (1)**	**Fear (2)**
Negative	-1.638***	0.769***	-1.065***	0.489***	-2.311***	0.722***	0.256	-0.023
	(0.176)	(0.162)	(0.170)	(0.147)	(0.158)	(0.120)	(0.169)	(0.118)
Age	0.021***	-0.012	0.016	-0.005	0.012	-0.008	0.017**	-0.001
	(0.008)	(0.007)	(0.008)	(0.006)	(0.007)	(0.005)	(0.008)	(0.005)
Male	-0.074	-0.176	-0.053	-0.249	0.213	-0.224	-0.276	-0.060
	(0.176)	(0.164)	(0.184)	(0.150)	(0.163)	(0.124)	(0.177)	(0.123)
Market Experience	0.093	-0.334	0.570***	-0.099	0.271	0.107	0.267	-0.148
	(0.189)	(0.186)	(0.204)	(0.165)	(0.169)	(0.127)	(0.189)	(0.130)
Constant	0.652**	1.755***	0.433	1.383***	1.187***	0.792***	0.504	0.760***
	(0.327)	(0.312)	(0.329)	(0.270)	(0.310)	(0.215)	(0.299)	(0.224)
N	391	391	400[22]	400	451	451	401	401
R^2	0.197	0.078	0.118	0.037	0.337	0.084	0.032	0.006

Table 5. Regression analysis of emotions.
Note: We report OLS coefficient estimates (robust standard errors). The dependent variable is the level of general affect (1) or the level of fear (2). The remaining variables are as defined above in the Table 1 notes. *** p<0.01, ** p<0.05.

We now examine risk taking behaviour. Since we have identified significant shifts of emotions, including fear, attributable to the priming manipulations employed in experiments E2 and E3, then to the extent that fear is a key factor explaining risk taking in this type of task, we have a basis for predicting corresponding shifts in risk taking in these two experiments.

Our results from the investment decisions are depicted in Figure 6. Similarly to Figure 5, each column refers to a given experiment: the top row shows responses to the risk task for each experiment while the bottom row shows responses to the ambiguity task, by experiment.

[22] We exclude two participants from the regression analysis of E2-W2 for not reporting properly whether they have any market experience.

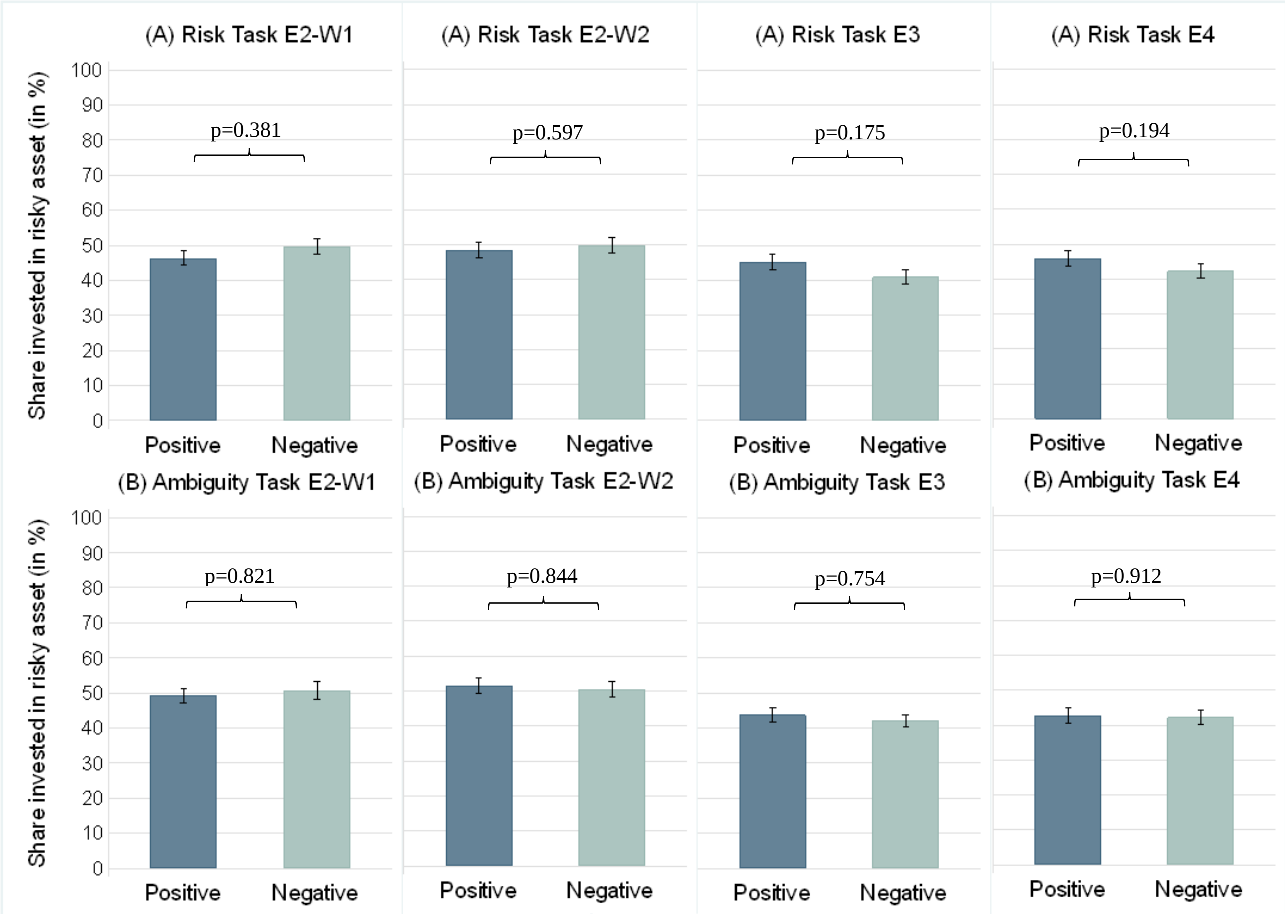


Figure 6. Average investment decisions (Experiments 2-4).
Notes: The figure shows average investments in the risk task (panel A), and the ambiguity task (panel B), by treatments for all new experiments. Error bars indicate standard errors of the mean.

As illustrated in Figure 6, average investment decisions are *not* significantly different across positive and negative treatments in any of the 8 comparisons (all Wilcoxon rank-sum p-values>0.175). We reach the same conclusion from OLS regressions reported in Table 6. We find either positive or negative effects of the negative prime on subsequent risk taking, but the effects are never statistically significant at the 5% level when we control for individual characteristics.

	E2-W1		E2-W2		E3		E4	
	Share invested in the risky asset							
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Negative	2.535 (2.775)	3.490 (3.015)	-0.150 (2.805)	0.956 (3.117)	-3.064 (2.469)	-4.349 (2.789)	-1.787 (2.685)	-3.301 (2.953)
Ambiguity	2.029 (1.359)	2.977 (1.759)	2.020 (1.216)	3.087 (1.780)	-0.187 (1.187)	-1.492 (1.832)	-1.751 (1.205)	-3.276 (1.847)
Negative × Ambiguity		-1.910 (2.721)		-2.211 (2.422)		2.571 (2.379)		3.028 (2.409)
Age	-0.063 (0.138)	-0.063 (0.138)	-0.073 (0.132)	-0.073 (0.132)	-0.195 (0.119)	-0.195 (0.119)	-0.149 (0.119)	-0.149 (0.119)
Male	2.307 (2.833)	2.307 (2.835)	5.883** (2.970)	5.883** (2.972)	12.949*** (2.531)	12.949*** (2.533)	5.978** (2.950)	5.978** (2.952)
Market Experience	2.816 (3.094)	2.816 (3.096)	2.399 (3.322)	2.399 (3.324)	3.470 (2.590)	3.470 (2.592)	-1.982 (2.987)	-1.982 (2.989)
Constant	46.019*** (5.491)	45.545*** (5.550)	47.341*** (5.981)	46.807*** (6.034)	43.352*** (4.871)	44.005*** (4.933)	49.154*** (5.074)	49.916*** (5.117)
N	782	782	800	800	902	902	802	802
Clusters	391	391	400	400	451	451	401	401
R^2	0.006	0.007	0.014	0.015	0.064	0.064	0.017	0.018

Table 6. Regression analysis of investment decisions.

Notes: We report OLS coefficient estimates (standard errors clustered on individuals). The dependent variable is the share invested as a percentage of the endowment. The remaining variables are as defined above in the Table 1 notes. *** p<0.01, ** p<0.05.

Did the priming manipulation have any effect on participants' expectations? The results from our analysis of the priming manipulations on the guessed share of winning balls and the self-reported level of optimism are reported in Table 7. While we find that older participants and participants who have some market experience are more optimistic, we do not find any evidence that participants' expectations are influenced by priming. This finding is in line with results from our Experiment 1, Cohn et al. (2015) and König-Kersting and Trautmann (2018).

	E2-W1		E2-W2		E3		E4	
	Guessed probability of success (1)	**General optimism (2)**	**Guessed probability of success (1)**	**General optimism (2)**	**Guessed probability of success (1)**	**General optimism (2)**	**Guessed probability of success (1)**	**General optimism (2)**
Negative	0.991 (1.514)	0.216 (0.155)	-0.767 (1.491)	0.240 (0.152)	1.310 (1.522)	-0.192 (0.138)	2.889 (1.597)	0.195 (0.153)
Age	0.038 (0.071)	0.025*** (0.007)	-0.061 (0.062)	0.014** (0.006)	0.046 (0.072)	0.012** (0.006)	0.020 (0.065)	0.022*** (0.007)
Male	-1.693 (1.515)	-0.014 (0.157)	-3.085** (1.478)	0.003 (0.154)	-0.623 (1.536)	0.150 (0.143)	1.222 (1.643)	-0.061 (0.160)
Market Experience	-0.520 (1.705)	0.520*** (0.183)	1.276 (1.596)	0.431** (0.181)	0.212 (1.668)	0.401*** (0.151)	0.194 (1.743)	0.334 (0.174)
Constant	47.777*** (2.746)	2.460*** (0.279)	51.941*** (2.841)	2.986*** (0.297)	43.337*** (2.859)	3.295*** (0.253)	44.387*** (2.805)	2.880*** (0.268)
N	391	391	400	400	451	451	401	401
R^2	0.006	0.076	0.012	0.041	0.003	0.041	0.009	0.048

Table 7. Regression analysis of expectations.

Notes: We report OLS coefficient estimates (robust standard errors). The dependent variables are: in Column 1 the percentage of winning balls in the ambiguity task, in Column 2 the degree of agreement to the statement "Overall, I expect more good things to happen to me than bad". The remaining variables are as defined above in the Table 1 notes. *** p<0.01, ** p<0.05.

Similar to our previous analysis, we assess the effect of emotions on investment behaviour using OLS regression. Our results are depicted in Table 8 for models including fear and in Table 9 for models using general affect. Eyeballing the results in Tables 8 and 9, we find no evidence of fear having any explanatory power on the investment decisions. On the contrary, our results for E2-W1, E2-W2 and E3 where emotions were significantly different between treatments reveal that, if anything, general affect is the channel through which emotions affect risk taking: specifically, the better participants feel, the more they invest (in line with e.g., Chou et al., 2007; Nguyen and Noussair, 2014; Williams et al., 2003; Yuen and Lee, 2003).

	E2-W1		E2-W2		E3		E4	
	Share invested in the risky asset							
	(1)	**(2)**	**(1)**	**(2)**	**(1)**	**(2)**	**(1)**	**(2)**
Negative		2.433		0.205		-2.606		-1.762
		(2.831)		(2.813)		(2.580)		(2.683)
Ambiguity	2.029	2.029	2.020	2.020	-0.187	-0.187	-1.751	-1.751
	(1.359)	(1.360)	(1.216)	(1.217)	(1.187)	(1.188)	(1.205)	(1.206)
Fear	0.308	0.133	-0.713	-0.725	-0.904	-0.634	1.111	1.104
	(0.954)	(0.972)	(0.942)	(0.945)	(0.979)	(1.022)	(1.188)	(1.181)
Age	-0.054	-0.061	-0.077	-0.077	-0.201	-0.200	-0.144	-0.148
	(0.140)	(0.138)	(0.131)	(0.132)	(0.118)	(0.119)	(0.117)	(0.117)
Male	2.388	2.330	5.704	5.702	12.706***	12.807***	6.208**	6.045**
	(2.847)	(2.842)	(2.957)	(2.958)	(2.532)	(2.536)	(2.968)	(2.949)
Market Experience	2.803	2.860	2.351	2.327	3.657	3.538	-1.841	-1.818
	(3.092)	(3.087)	(3.334)	(3.347)	(2.585)	(2.584)	(2.989)	(2.992)
Constant	46.482***	45.786***	48.421***	48.343***	42.767***	43.855***	47.198***	48.315***
	(5.503)	(5.672)	(5.783)	(6.022)	(4.827)	(4.940)	(4.995)	(5.170)
N	782	782	800	800	902	902	802	802
Clusters	391	391	400	400	451	451	401	401
R^2	0.005	0.007	0.016	0.016	0.063	0.064	0.018	0.019

Table 8. Regression analysis of investment decisions on fear.

Notes: We report OLS coefficient estimates (standard errors clustered on individuals). The dependent variable is the share invested as a percentage of the endowment. Fear is the self-reported measurement of fear (from 0: no fear to 6: high levels of fear). The remaining variables are as defined above in the Table 1 notes. *** p<0.01, ** p<0.05.

	E2-W1		E2-W2		E3		E4	
	Share invested in the risky asset							
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Negative		7.050**		2.134		-0.061		-1.910
		(3.151)		(2.985)		(2.877)		(2.678)
Ambiguity	2.029	2.029	2.020	2.020	-0.187	-0.187	-1.751	-1.751
	(1.359)	(1.360)	(1.216)	(1.217)	(1.187)	(1.188)	(1.205)	(1.206)
General affect	1.961***	2.756***	1.963**	2.143**	1.308**	1.300	0.440	0.481
	(0.746)	(0.856)	(0.828)	(0.884)	(0.599)	(0.700)	(0.838)	(0.833)
Age	-0.091	-0.122	-0.107	-0.106	-0.211	-0.211	-0.152	-0.157
	(0.140)	(0.138)	(0.130)	(0.130)	(0.118)	(0.118)	(0.121)	(0.121)
Male	2.519	2.511	5.979**	5.996**	12.670***	12.672***	6.275**	6.111**
	(2.817)	(2.788)	(2.943)	(2.938)	(2.529)	(2.542)	(2.959)	(2.942)
Market Experience	2.346	2.561	1.509	1.178	3.117	3.118	-2.125	-2.110
	(3.040)	(3.011)	(3.326)	(3.359)	(2.592)	(2.594)	(2.986)	(2.987)
Constant	47.249***	44.221***	47.400***	46.412***	41.777***	41.809***	47.733***	48.911***
	(5.176)	(5.423)	(5.572)	(5.813)	(4.667)	(4.825)	(4.885)	(5.072)
N	782	782	800	800	902	902	802	802
Clusters	391	391	400	400	451	451	401	401
R^2	0.020	0.030	0.027	0.028	0.069	0.069	0.017	0.018

Table 9. Regression analysis of investment decisions on general affect.

Notes: We report OLS coefficient estimates (standard errors clustered on individuals). The dependent variable is the share invested as a percentage of the endowment. General affect is the self-reported measurement of affect (from -4: negative to 4: positive). The remaining variables are as defined above in the Table 1 notes. *** p<0.01, ** p<0.05.

4. Composite analysis

The disadvantage of looking for an effect separately in each experiment is that it does not provide cumulative evidence for the underlying effect, and to overcome this, several studies have argued for assessing replication using meta-analytic estimates (e.g., Braver et al., 2014; Camerer et al., 2018; Open Science Collaboration, 2015; Stanley and Spence, 2014).[23] We follow this approach as a final step in order to estimate a current best guess of the overall effect size due to priming in the risk and ambiguity tasks combining evidence from our experiments with effect sizes reported in the original Cohn et al. study (2015), and in the study by König-Kersting and Trautmann (2018).[24] We use standard random effects[25] meta-analysis procedures to determine average effect sizes using Cohen's *d* (Cohen, 1988): the mean difference in risk taking between the positive and negative treatments, divided by the pooled

[23] In Appendix D, we report a series of alternative analyses to estimate the underlying effect such as confidence intervals, prediction intervals and Bayesian tests. Results are broadly in line with what we report in the main text.
[24] Since most of the studies included in the composite analysis are generated from the same group of researchers, we do not consider this exercise as a sufficient condition to obtain a definitive estimate of the underlying effect size; however, we believe it is a useful step in the right direction.
[25] A random effects model is more suitable for our purposes than the fixed effects alternative that assumes effect sizes only differ by sampling error. Our conclusions do not change if we consider a fixed effects model instead.

standard deviation. The results from our composite analysis are depicted in Figure 7 for the risk (Panel A) and ambiguity (Panel B) tasks.

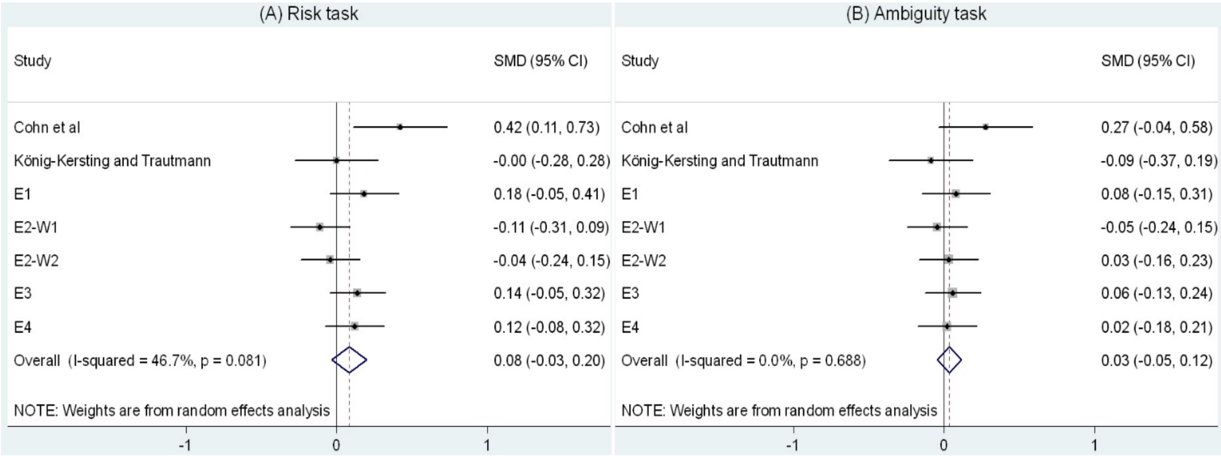


Figure 7. Composite analysis for the risk (A) and ambiguity (B) variants of the task.
Notes: Effect sizes and 95% confidence intervals are shown per experiment. A positive effect size indicates that the mean risk taking was higher in the positive compared to the negative treatment.

As illustrated in Figure 7, the overall effect size is 0.08 95% CI [-0.03, 0.20] in the risk task and 0.03 95% CI [-0.05, 0.12] in the ambiguity task. The direction of the effect is positive in both cases, consistent with primes of negative experiences reducing risk taking; however, the overall effect is not statistically distinguishable from zero for either variant of the task.

5. Conclusions

Using a range of priming techniques from psychology and economics, we found that priming has no significant overall effect on risk preferences in an MTurk population. Crucially, this result holds independently of whether we were able to successfully manipulate the level of emotions. Furthermore, while we do find some relationship between emotional responses and risk taking, we reject the premise that, in our environment, increased fear is associated with lower levels of risk taking; instead, our results speak in favour of an influence of general affect, of the form that: the better you feel, the more risk you take.

Our experiments were inspired partly by the findings of Cohn et al. (2015) who reported a significant impact of priming ‘boom’ or ‘bust’ scenarios on risk taking in a sample of professional investors. While our experiments include priming techniques very close to those of Cohn et al. (2015) (Experiment 1) and use the same procedures for measuring risk taking, our experimental designs depart importantly from theirs by using a different subject pool (i.e., MTurk). Because of this we do not interpret our results as a failure to replicate their original findings. Rather, our results lead us to question the generalisability of the priming effects observed by Cohn et al. (2015) from financial professionals to a more diverse (and less specialist) MTurk population. As well as suggesting this boundary, however, our findings add to the evidence highlighting the context sensitivity of priming effects and to the evidence concerning the emotional underpinnings of risk taking.

References

Aldrovandi, S., Kusev, P., Hill, T., & Vlaev, I. (2017). Context moderates priming effects on financial risk taking. *Risks*, *5*(1), 18.

Alevy, J. E., Haigh, M. S., & List, J. A. (2007). Information cascades: Evidence from a field experiment with financial market professionals. *The Journal of Finance*, *62*(1), 151-180.

Amir, O., & Rand, D. G. (2012). Economic games on the internet: The effect of $1 stakes. *PloS one*, *7*(2), e31461.

Arechar, A. A., Gächter, S., & Molleman, L. (2018). Conducting interactive experiments online. *Experimental economics*, *21*(1), 99-131.

Ball, S. B., & Cech, P. A. (1996). Subject pool choice and treatment effects in economic laboratory research. *Research in Experimental Economics*, *6*(3), 239-292.

Bargh, J. A. (2006). What have we been priming all these years? On the development, mechanisms, and ecology of nonconscious social behavior. *European journal of social psychology*, *36*(2), 147-168.

Benjamin, D. J., Choi, J. J., & Strickland, A. J. (2010). Social identity and preferences. *American Economic Review*, *100*(4), 1913-28.

Berinsky, A. J., Huber, G. A., & Lenz, G. S. (2012). Evaluating online labor markets for experimental research: Amazon. com's Mechanical Turk. *Political Analysis*, *20*(3), 351-368.

Bolton, G. E., Ockenfels, A., & Thonemann, U. W. (2012). Managers and students as newsvendors. *Management Science*, *58*(12), 2225-2233.

Bosman, R., & Van Winden, F. (2002). Emotional hazard in a power- to- take experiment. *The Economic Journal*, *112*(476), 147-169.

Bradley, M. M., & Lang, P. J. (1994). Measuring emotion: the self-assessment manikin and the semantic differential. *Journal of behavior therapy and experimental psychiatry*, *25*(1), 49-59.

Braver, S. L., Thoemmes, F. J., & Rosenthal, R. (2014). Continuously cumulating meta-analysis and replicability. *Perspectives on Psychological Science*, *9*(3), 333-342.

Buhrmester, M., Kwang, T., & Gosling, S. D. (2011). Amazon's Mechanical Turk: A new source of inexpensive, yet high-quality, data?. *Perspectives on psychological science*, *6*(1), 3-5.

Callen, M., Isaqzadeh, M., Long, J. D., & Sprenger, C. (2014). Violence and risk preference: Experimental evidence from Afghanistan. *American Economic Review*, *104*(1), 123-48.

Camerer, C. F., Dreber, A., Holzmeister, F., Ho, T. H., Huber, J., Johannesson, M., ... & Altmejd, A. (2018). Evaluating the replicability of social science experiments in Nature and Science between 2010 and 2015. *Nature Human Behaviour*, 1.

Casler, K., Bickel, L., & Hackett, E. (2013). Separate but equal? A comparison of participants and data gathered via Amazon's MTurk, social media, and face-to-face behavioral testing. *Computers in Human Behavior*, *29*(6), 2156-2160.

Chandler, J., Mueller, P., & Paolacci, G. (2014). Nonnaïveté among Amazon Mechanical Turk workers: Consequences and solutions for behavioral researchers. *Behavior research methods*, *46*(1), 112-130.

Chandler, J., Paolacci, G., Peer, E., Mueller, P., & Ratliff, K. A. (2015). Using nonnaive participants can reduce effect sizes. *Psychological science*, *26*(7), 1131-1139.

Chou, K. L., Lee, T., & Ho, A. H. (2007). Does mood state change risk taking tendency in older adults?. *Psychology and aging*, *22*(2), 310.

Clifford, S., & Jerit, J. (2014). Is there a cost to convenience? An experimental comparison of data quality in laboratory and online studies. *Journal of Experimental Political Science*, *1*(2), 120-131.

Cohen, J. (1988). Statistical power analysis for the behavioral sciences (2nd ed.). Hillsdale, NJ: Erlbaum.

Cohn, A., Engelmann, J., Fehr, E., & Maréchal, M. A. (2015). Evidence for countercyclical risk aversion: an experiment with financial professionals. *American Economic Review*, 105(2), 860-85.

Cohn, A., & Maréchal, M.A. (2016). Priming in economics. *Current Opinion in Psychology*, *12*, 17-21.

Crump, M. J., McDonnell, J. V., & Gureckis, T. M. (2013). Evaluating Amazon's Mechanical Turk as a tool for experimental behavioral research. *PloS one*, *8*(3), e57410.

D'Acunto, Francesco, Identity, Overconfidence, and Investment Decisions (August 7, 2015a). Available at SSRN: https://ssrn.com/abstract=2641182 or http://dx.doi.org/10.2139/ssrn.2641182

D'Acunto, Francesco, Tear Down This Wall Street: The Effect of Anti-Market Ideology on Investment Decisions (December 10, 2015b). Available at SSRN: https://ssrn.com/abstract=2705545or http://dx.doi.org/10.2139/ssrn.2705545

Doyen, S., Klein, O., Pichon, C. L., & Cleeremans, A. (2012). Behavioral priming: it's all in the mind, but whose mind?. *PloS one*, *7*(1), e29081.

Drichoutis, A. C., & Nayga Jr, R. M. (2013). Eliciting risk and time preferences under induced mood states. *The Journal of Socio-Economics*, *45*, 18-27.

Erb, H. P., Bioy, A., & Hilton, D. J. (2002). Choice preferences without inferences: Subconscious priming of risk attitudes. *Journal of Behavioral Decision Making*, *15*(3), 251-262.

Faul, F., Erdfelder, E., Buchner, A., & Lang, A. G. (2009). Statistical power analyses using G* Power 3.1: Tests for correlation and regression analyses. *Behavior research methods*, *41*(4), 1149-1160.

Fehr, H., Epper, T., Bruhin, A., & Schubert, R. (2007). *Risk and rationality: The effect of incidental mood on probability weighting* (No. 0703). Working Paper, Socioeconomic Institute, University of Zurich.

Frechette, G. (2015). Laboratory Experiments: Professionals versus Students. In *Handbook of Experimental Economic Methodology*. Oxford University Press.

Gilad, D., & Kliger, D. (2008). Priming the risk attitudes of professionals in financial decision making. *Review of Finance*, 567-586.

Gneezy, U., & Potters, J. (1997). An experiment on risk taking and evaluation periods. *The Quarterly Journal of Economics*, *112*(2), 631-645.

Gomes, C. M., & McCullough, M. E. (2015). The effects of implicit religious primes on dictator game allocations: A preregistered replication experiment. *Journal of Experimental Psychology: General*, *144*(6), e94.

Goodman, J. K., Cryder, C. E., & Cheema, A. (2013). Data collection in a flat world: The strengths and weaknesses of Mechanical Turk samples. *Journal of Behavioral Decision Making*, *26*(3), 213-224.

Guiso, L., Sapienza, P., & Zingales, L. (2013). *Time varying risk aversion* (No. w19284). National Bureau of Economic Research.

Haigh, M. S., & List, J. A. (2005). Do professional traders exhibit myopic loss aversion? An experimental analysis. *The Journal of Finance*, *60*(1), 523-534.

Hamilton, R. W., & Biehal, G. J. (2005). Achieving your goals or protecting their future? The effects of self-view on goals and choices. *Journal of Consumer Research*, *32*(2), 277-283.

Harris, J., & Blair, E. A. (2006). Functional compatibility risk and consumer preference for product bundles. *Journal of the Academy of Marketing Science*, *34*(1), 19-26.

Hauser, D., Paolacci, G., & Chandler, J. J. (2018). Common Concerns with MTurk as a Participant Pool: Evidence and Solutions. *PsyArXiv. September, 1*.

Henson, R. N. A., & Rugg, M. D. (2003). Neural response suppression, haemodynamic repetition effects, and behavioural priming. *Neuropsychologia*, *41*(3), 263-270.

Hirshleifer, D., & Shumway, T. (2003). Good day sunshine: Stock returns and the weather. The Journal of Finance, 58(3), 1009-1032.

Hockey, G. R. J., John Maule, A., Clough, P. J., & Bdzola, L. (2000). Effects of negative mood states on risk in everyday decision making. *Cognition & Emotion*, *14*(6), 823-855.

Horton, J. J., Rand, D. G., & Zeckhauser, R. J. (2011). The online laboratory: Conducting experiments in a real labor market. *Experimental economics*, *14*(3), 399-425.

Isen, A. M., & Geva, N. (1987). The influence of positive affect on acceptable level of risk: The person with a large canoe has a large worry. *Organizational Behavior and Human Decision Processes*, *39*(2), 145-154.

Isen, A. M., & Patrick, R. (1983). The effect of positive feelings on risk taking: When the chips are down. *Organizational behavior and human performance*, *31*(2), 194-202.

Kamstra, M. J., Kramer, L. A., & Levi, M. D. (2003). Winter blues: A SAD stock market cycle. *American Economic Review*, *93*(1), 324-343.

König-Kersting, C., & Trautmann, S. T. (2018). Countercyclical risk aversion: Beyond financial professionals. *Journal of Behavioral and Experimental Finance*.

Kusev, P., van Schaik, P., & Aldrovandi, S. (2012). Preferences induced by accessibility: Evidence from priming. Journal of Neuroscience, Psychology, and Economics, 5(4), 250.

Lerner, J. S., Gonzalez, R. M., Small, D. A., & Fischhoff, B. (2003). Effects of fear and anger on perceived risks of terrorism: A national field experiment. *Psychological science*, *14*(2), 144-150.

Lerner, J. S., & Keltner, D. (2000). Beyond valence: Toward a model of emotion-specific influences on judgement and choice. *Cognition & emotion*, *14*(4), 473-493.

Levay, K. E., Freese, J., & Druckman, J. N. (2016). The demographic and political composition of Mechanical Turk samples. *Sage Open*, *6*(1), 2158244016636433.

Loewenstein, G. F., Weber, E. U., Hsee, C. K., & Welch, N. (2001). Risk as feelings. *Psychological bulletin*, *127*(2), 267.

Ludvig, E. A., Madan, C. R., & Spetch, M. L. (2015). Priming memories of past wins induces risk seeking. *Journal of Experimental Psychology: General*, *144*(1), 24.

MacDonald, J. A., Sandry, J., & Rice, S. (2012). Self-construal priming affects speed of retrieval from short-term memory. *PloS one*, *7*(11), e50007.

Mandel, N. (2003). Shifting selves and decision making: The effects of self-construal priming on consumer risk-taking. *Journal of Consumer Research*, *30*(1), 30-40.

Mason, W., & Suri, S. (2012). Conducting behavioral research on Amazon's Mechanical Turk. *Behavior research methods*, *44*(1), 1-23.

Molden, D. C. (2014). Understanding priming effects in social psychology: What is "social priming" and how does it occur?. *Social Cognition*, *32*(Supplement), 1-11.

Morris, R. R., Dontcheva, M., Finkelstein, A., & Gerber, E. (2013, September). Affect and creative performance on crowdsourcing platforms. In *Affective computing and intelligent interaction (ACII), 2013 humaine association conference on*(pp. 67-72). IEEE.

Newell, B. R., & Shanks, D. R. (2014). Unconscious influences on decision making: A critical review. *Behavioral and Brain Sciences*, *37*(1), 1-19.

Newell, B. R., & Shaw, B. (2017). Priming Risky Choice: Do Risk Preferences Need Inferences?. *Journal of Behavioral Decision Making*, *30*(2), 332-346.

Nguyen, Y., & Noussair, C. N. (2014). Risk aversion and emotions. *Pacific economic review*, *19*(3), 296-312.

Open Science Collaboration. (2015). Estimating the reproducibility of psychological science. *Science*, *349*(6251), aac4716.

Paolacci, G., & Chandler, J. (2014). Inside the Turk: Understanding Mechanical Turk as a participant pool. *Current Directions in Psychological Science*, *23*(3), 184-188.

Paolacci, G., Chandler, J., & Ipeirotis, P. G. (2010). Running experiments on Amazon Mechanical Turk. *Judgment and Decision Making*, *5*(5), 411-419.

Preece, J., & Stoddard, O. (2015). Why women don't run: Experimental evidence on gender differences in political competition aversion. *Journal of Economic Behavior & Organization*, *117*, 296-308.

Rand, D. G. (2012). The promise of Mechanical Turk: How online labor markets can help theorists run behavioral experiments. *Journal of theoretical biology*, *299*, 172-179.

Rand, D. G. (2018). Non-naïvety may reduce the effect of intuition manipulations. *Nature Human Behaviour*, *2*(9), 602.

Rand, D. G., Peysakhovich, A., Kraft-Todd, G. T., Newman, G. E., Wurzbacher, O., Nowak, M. A., & Greene, J. D. (2014). Social heuristics shape intuitive cooperation. *Nature communications*, *5*, 3677.

Shanks, D. R., Newell, B. R., Lee, E. H., Balakrishnan, D., Ekelund, L., Cenac, Z., ... & Moore, C. (2013). Priming intelligent behavior: An elusive phenomenon. *PloS one*, *8*(4), e56515.

Shanks, D. R., Vadillo, M. A., Riedel, B., Clymo, A., Govind, S., Hickin, N., ... & Puhlmann, L. (2015). Romance, risk, and replication: Can consumer choices and risk-taking be primed by mating motives?. *Journal of Experimental Psychology: General*, *144*(6), e142.Scheier, M. F., Carver, C. S., & Bridges, M. W. (1994). Distinguishing optimism from neuroticism (and trait anxiety, self-mastery, and self-esteem): a reevaluation of the Life Orientation Test. *Journal of personality and social psychology*, *67*(6), 1063.

Stanley, D. J., & Spence, J. R. (2014). Expectations for replications: Are yours realistic?. *Perspectives on Psychological Science*, *9*(3), 305-318.

Stewart, N., Chandler, J., & Paolacci, G. (2017). Crowdsourcing samples in cognitive science. *Trends in cognitive sciences*.

Tversky, A., & Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases. *Science*, *185*(4157), 1124-1131.

Vadillo, M. A., Hardwicke, T. E., & Shanks, D. R. (2016). Selection bias, vote counting, and money-priming effects: A comment on Rohrer, Pashler, and Harris (2015) and Vohs (2015).

Welsh, D. T., & Ordóñez, L. D. (2014). Conscience without cognition: The effects of subconscious priming on ethical behavior. *Academy of Management Journal*, *57*(3), 723-742.

Williams, S., Zainuba, M., & Jackson, R. (2003). Affective influences on risk perceptions and risk intention. *Journal of Managerial Psychology*, *18*(2), 126-137.

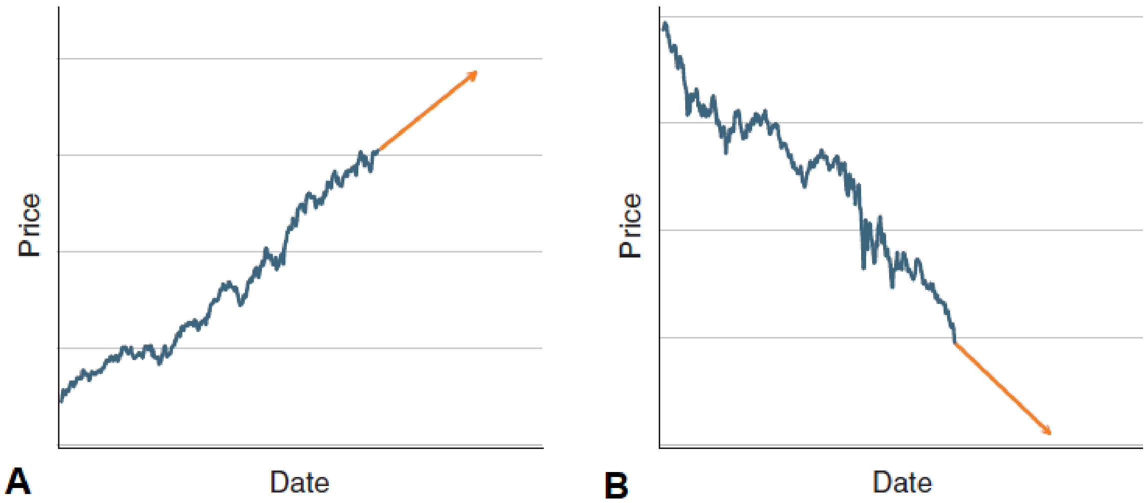
Yuen, K. S., & Lee, T. M. (2003). Could mood state affect risk-taking decisions?. *Journal of affective disorders*, *75*(1), 11-18.

Appendix A

Appendix A reports the instructions from Experiment 1 (Priming questions, Emotions and Investment task)

Priming

In this study you will be requested to answer several questions regarding the following scenario. Imagine you find yourself in a continuing stock market boom (crash). You expect the positive (negative) development to continue as indicated by the arrow in the graph.

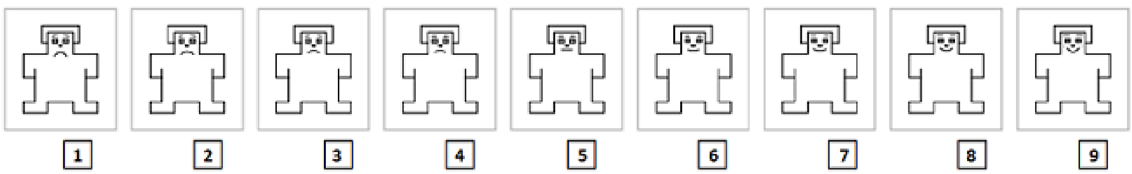


Note: Panel A (B) was used in the positive (negative) treatment. Adapted from Figure 1 in Cohn et al. (2015).

1. Would you sell/buy individual stocks? Explain briefly why.
2. Would you invest in gold or other precious metals? Explain briefly why.
3. Would you deposit part of your assets on your savings account? Explain briefly why.
4. Would you consider purchasing real estate (for instance a house)? Explain briefly why.

Emotions

1. How are you feeling at the moment? Please select one of the numbers to indicate how you feel



2. To what extent are you experiencing the emotion "fear" at the moment?

1-Not at all 2 3 4 5 6 7-A lot

Investment task

We now proceed to the **bonus** part. In this part you will make two investment decisions; by doing so you will win or lose money. Note that only **one of the two** investment decisions will be paid out at the end of the study. The decision that will be paid out is determined randomly.

First Investment Decision

Your initial endowment amounts to $200. You have to decide what share of this you would like to invest in a risky asset. You can keep the remaining amount that you do not invest.

The investment decision works like this

We will **randomly -without looking into the box-** draw one of the balls out of the big plastic box (see picture). The big plastic box contains red, blue and yellow balls in an unknown ratio. If a **yellow ball** is drawn, you **win** and receive 2.5 times the amount you invested. If **a red or a blue ball** is drawn, you will **lose** your investment and you will not get anything back.

Your earnings are thus calculated as follows
• If you win (yellow ball is drawn):
Your earnings = $200 minus investment plus (**2.5** x investment)
• If you lose (a red or blue ball is drawn):
Your earnings = $200 minus investment

How many $ would you like to invest (0 - 200)?

What is your guess of the share of yellow (winning) balls in the big plastic box? (In percent 0-100)

<u>Second investment decision</u>

Your initial endowment amounts again to $200. You may now decide what share of this you would like to invest in a risky asset. You may keep the remaining amount that you do not invest.

<u>The investment decision works like this</u>

Again we will **randomly -without looking into the box-** draw one of the balls out of the small plastic box (see picture). The small plastic box contains **one red and one yellow ball**. If the **yellow ball** is drawn, you **win** and receive 2.5 times the amount you have invested. If the **red ball** is drawn, you will **lose** your investment and you will not get anything back.

Your earnings are thus calculated as follows
• If you win (yellow ball is drawn)
Your earnings = $200 minus investment plus (**2.5** x investment)
• If you lose (a red or blue ball is drawn)
Your earnings = $200 minus investment

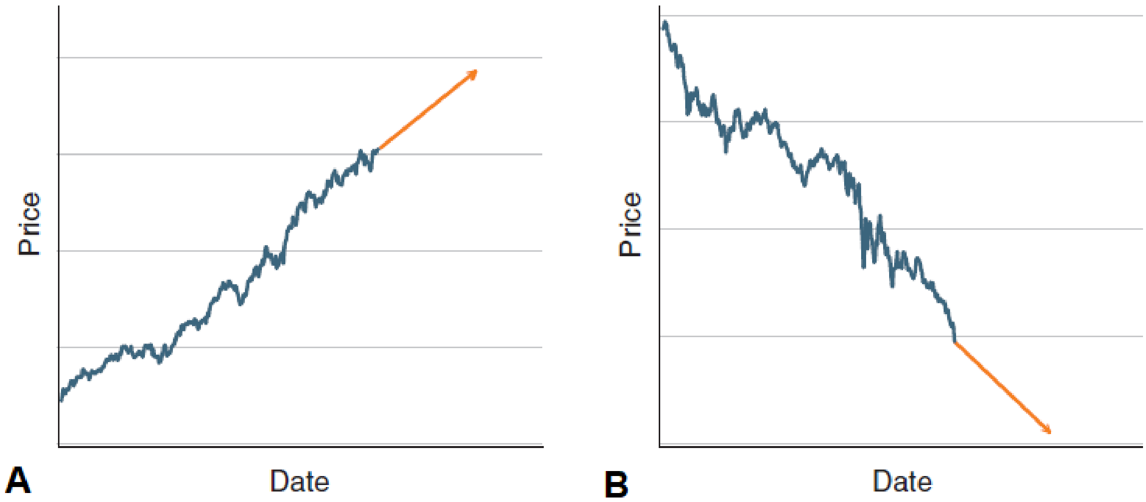
How many $ would you like to invest (0 - 200)?

Appendix B

Appendix B reports the priming techniques used in Experiments 2-4

Experiment 2

In this study you will be requested to answer several questions regarding the following scenario. Imagine you find yourself in a continuing stock market boom (crash). You expect the positive (negative) development to continue as indicated by the arrow in the graph.



Note: Panel A (B) was used in the positive (negative) treatment. Adapted from Figure 1 in Cohn et al. (2015).

1. Do you think that you would sell individual stocks? Explain briefly why.
2. Would you expect that you would transfer part of your investments in a savings account instead? Explain briefly why.
3. How risky do you consider it is for you to continue investing in the stock market? Explain briefly why.
4. How would you expect you would feel? Explain briefly.
5. How disappointed do you expect you would feel?
   How unhappy do you expect you would feel?
   How stressed do you expect you would feel?
   How pessimistic do you expect you would feel?
   How worried do you expect you would feel?
   1-Not at all 2 3 4 5 6 7-A lot
6. Do you think it is likely that you would invest again in the stock market in the future? Explain briefly why/why not.
7. Please list the different ways in which your life would be affected by the stock market boom (crash).
8. Please write down your feelings about this experience of a stock market boom (crash) happening to you.

Experiment 3

Positive priming: In this study we would first like you to spend a few minutes describing a positive experience you had involving winning money. This could be anything, for example winning money from investing, from gambling, from a lottery ticket or from any other situation that resulted in a financial gain for you.

Negative priming: In this study we would first like you to spend a few minutes describing a negative experience you had involving losing money. This could be anything, for example losing money from investing, from gambling, from a lottery ticket or from any other situation that resulted in a financial loss for you.

Experiment 4

Negative priming: (vignette in which risk taking is associated with imprudence and loss)

Risk averse: "Danny is a responsible, reasonable, and reliable person, who is trustworthy and level-headed. In his last journey, he has chosen to go to a Greek island. In the first evening, he decided to join a guided tour provided by his hotel for the visitors. During the tour, the visitors arrived at a casino. While the other visitors decided to bet at the casino, Danny decided to avoid betting, and go sight-seeing instead. When he reunited with the visitors who went to the casino he found out that they lost a lot of money, and will therefore have to end their vacation sooner than they had planned to. Danny was satisfied with his reasonable decision not to go to the casino, his prudence made the rest of his joyful stay at the island possible, in contrast to the rest of the group."

Please proceed to the memorization task when ready, where you will be asked to recollect as many **adjectives** as you can from the story you just read.

Positive priming: (vignette in which risk taking is associated with adventure and winning)

Risk seeking: "Danny is an adventurous, courageous, and initiatory person, who is fond of new experiences, likes thrills and does not hesitate to take risks. In his last journey he went to Turkey and, one evening, he decided to go betting at a casino. He entered the casino with $4,000 and, as suitable for a daring person, decided to play the roulette, a game with a high risk factor. He was lucky that day, and collected $30,000. Danny left the casino satisfied by the initiative he has taken. He decided to celebrate with a fancy dinner at the hotel's bar, and afterwards went up to his room happy and satisfied."

Please proceed to the memorization task when ready, where you will be asked to recollect as many **adjectives** as you can from the story you just read.

Appendix C

Appendix C reports further regression tables. Table C1 reports regression results from Experiment 1, when using Investment Instrument Frequency as a control variable. Tables C2 and C3 report regression analysis including both emotions simultaneously. Table C2 corresponds to Table 3 and Table C3 to Tables 8 and 9.

	Share invested in the risky asset			
	(1)	**(2)**	**(3)**	**(4)**
Negative	-4.623 (3.365)	-6.298 (3.661)	-4.816 (3.360)	-6.490 (3.664)
Ambiguity	4.920*** (1.424)	3.291 (2.083)	4.920*** (1.424)	3.291 (2.083)
Negative × Ambiguity		3.349 (2.837)		3.349 (2.837)
Age	-0.243 (0.133)	-0.243 (0.133)	-0.218 (0.131)	-0.218 (0.131)
Male	6.086 (3.342)	6.086 (3.345)	5.214 (3.375)	5.214 (3.378)
Investment Instruments	4.069 (3.675)	4.069 (3.678)	7.620 (4.372)	7.620 (4.376)
Constant	53.799*** (6.109)	54.613*** (6.123)	55.038*** (5.827)	55.853*** (5.844)
N	588	588	588	588
Clusters	294	294	294	294
R^2	0.031	0.032	0.036	0.036

Table C1. Regression analysis of investment decisions.

Notes: We report OLS coefficient estimates (standard errors clustered on individuals). The dependent variable is the share invested as a percentage of the endowment. “Negative” is a dummy for the negative prime treatment and “Ambiguity” is a dummy for the ambiguity task. The interaction term “Negative × Ambiguity” allows the treatment effect to be different in the risk and ambiguity variants. “Age” is the individual’s age in years, and “Male” is a gender dummy. “Investment Instruments” in Columns (1) and (2) is a dummy for individuals who answer at least “Once per year” in the question “How often, if at all, do you deal with investment instruments (purchase and sale)?”, whereas in Columns (3) and (4) they answer at least “Once a month” (Answers range from “Never” to “Daily”). *** p<0.01, ** p<0.05.

	General affect	Fear	Share invested in risky asset	
	(1)	(2)	(3)	(4)
Negative	-0.262 (0.180)	-0.089 (0.139)		-4.694 (3.369)
Ambiguity			4.920*** (1.425)	4.920*** (1.427)
General affect			1.051 (1.202)	0.883 (1.209)
Fear			-0.634 (1.615)	-0.783 (1.628)
Age	0.000 (0.008)	-0.014** (0.006)	-0.214 (0.137)	-0.236 (0.136)
Male	-0.056 (0.182)	-0.285** (0.144)	6.051 (3.396)	6.104 (3.383)
Market Experience	0.829*** (0.213)	-0.071 (0.158)	-1.217 (3.765)	-1.113 (3.773)
Constant	0.871*** (0.313)	1.448*** (0.267)	53.303*** (6.068)	56.600*** (6.402)
N	294	294	588	588
Clusters			294	294
R^2	0.068	0.034	0.026	0.031

Table C2. Regression analysis of emotions in Experiment 1.

Notes: We report OLS coefficient estimates (robust standard errors for Columns 1 and 2, clustered on individuals for Columns 3-4). The dependent variables are: in Column 1 the level of general affect (from -4: negative to 4: positive), in Column 2 the level of fear (from 0: no fear to 6: high levels of fear), in columns 3 and 4 the share invested as a percentage of the endowment. The remaining variables are as defined in Table C1. *** p<0.01, ** p<0.05.

	E2-W1		E2-W2		E3		E4	
	Share invested in the risky asset							
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Negative		6.898**		2.097		-0.020		-1.963
		(3.145)		(2.976)		(2.898)		(2.672)
Ambiguity	2.029	2.029	2.020	2.020	-0.187	-0.187	-1.751	-1.751
	(1.360)	(1.360)	(1.217)	(1.217)	(1.188)	(1.188)	(1.206)	(1.206)
General affect	2.794***	3.547***	2.063**	2.227**	1.265	1.263	0.777	0.822
	(0.826)	(0.931)	(0.890)	(0.944)	(0.647)	(0.728)	(0.919)	(0.914)
Fear	1.938	1.881	0.296	0.258	-0.175	-0.174	1.483	1.497
	(1.041)	(1.019)	(0.987)	(0.985)	(1.054)	(1.061)	(1.272)	(1.263)
Age	-0.085	-0.115	-0.107	-0.106	-0.212	-0.212	-0.156	-0.161
	(0.139)	(0.137)	(0.130)	(0.130)	(0.118)	(0.118)	(0.120)	(0.120)
Male	2.921	2.901	6.058**	6.065**	12.640***	12.641***	6.463**	6.295**
	(2.811)	(2.786)	(2.909)	(2.905)	(2.526)	(2.541)	(2.957)	(2.940)
Market Experience	2.922	3.115	1.477	1.156	3.146	3.146	-1.996	-1.980
	(3.023)	(2.989)	(3.313)	(3.349)	(2.579)	(2.581)	(2.985)	(2.988)
Constant	43.248***	40.403***	46.930***	46.019***	41.981***	41.991***	46.403***	47.601***
	(5.541)	(5.782)	(5.644)	(5.896)	(4.830)	(4.946)	(5.018)	(5.200)
N	782	782	800	800	902	902	802	802
Clusters	391	391	400	400	451	451	401	401
R^2	0.027	0.038	0.027	0.029	0.069	0.069	0.020	0.021

Table C3. Regression analysis of emotions in Experiments 2-4.

Notes: We report OLS coefficient estimates (standard errors clustered on individuals). The dependent variable is the share invested as a percentage of the endowment. "General affect" is the self-reported measurement of affect (from -4: negative to 4: positive) and "Fear" is the self-reported measurement of fear (from 0: no fear to 6: high levels of fear). The remaining variables are as defined in Table C1. *** p<0.01, ** p<0.05.

	Age	Gender (Male proportion)	Market Experience
E1	35.4	53%	67%
E2-W1	36.5	51%	65%
E2-W2	38.5	49%	70%
E3	36.1	48%	60%
E4	37.2	45%	59%
p-values	0.001	0.275	0.005

Table C4. Randomization check across experiments (chi-square test for binary variables gender and market experience, Kruskal-Wallis test for Age).

	Age		p-values	Gender (Male proportion)		p-values	Market Experience		p-values
	Positive	**Negative**		**Positive**	**Negative**		**Positive**	**Negative**	
E1	36.6	34.2	0.101	52%	55%	0.620	68%	66%	0.652
E2-W1	36.1	37.0	0.329	51%	51%	0.957	66%	63%	0.521
E2-W2	38.9	38.1	0.449	47%	50%	0.562	65%	75%	0.041
E3	36.3	35.8	0.654	47%	48%	0.803	62%	58%	0.431
E4	37.8	36.7	0.321	49%	41%	0.101	60%	58%	0.702

Table C5. Randomization check across treatments for a given experiment (chi-square test for binary variables gender and market experience, ranksum test for variable age).

Appendix D

Although p-values are an informative aspect of evaluating the success of a replication, it might be the case that many of the replication studies just fall short of the 0.05 cut-off criterion (see the discussion in Braver et al., 2014; Camerer et al., 2018; Open Science Collaboration, 2015). To this end, we report a series of complementary measurements to assess the replicability of our studies.

For each experiment, we report t-tests with their accompanying p-values. We further complement our analysis using Bayesian methods (Lee and Wagenmakers, 2014; Morey and Rouder, 2011; Rouder et al., 2009) that have increasingly been used as an alternative approach to standard hypothesis testing (e.g., Camerer et al., 2018; Newell and Shaw, 2017; Shanks et al., 2013, 2015). More specifically, for each experiment we compute a "Bayes factor", which is the ratio of the probability of the data given the null hypothesis versus the probability of the data given the experimental hypothesis. A Bayes factor of between 1:1 and 3:1 is taken to provide 'anecdotal' evidence in favour of the null, whereas factors of between 3:1 and 10:1 provide 'substantial' support and factors between 10:1 and 30:1 provide 'strong' support in favour of the null (Wetzels et al., 2011). We report results from both analyses in Tables D1 (t-tests) and D2 (Bayes factors), respectively. We find no evidence of countercyclical risk aversion either in the risk or the ambiguity variant of the task (all t-test p-values>0.05, all Bayes factors>1 both for one-tailed and two-tailed tests).[1]

	RISK			AMBIGUITY		
	t	P-value		t	P-value	
Study		**Two-sided**	**One-sided**		**Two-sided**	**One-sided**
E1	1.552	0.122	0.061	0.671	0.503	0.251
E2-W1	-1.100	0.272	0.864	-0.455	0.650	0.675
E2-W2	-0.436	0.663	0.668	0.316	0.752	0.376
E3	1.456	0.146	0.073	0.605	0.545	0.273
E4	1.196	0.232	0.116	0.191	0.849	0.424

Table D1. Results from t-tests.

	RISK		AMBIGUITY	
	BF_{01}		BF_{01}	
Study	**Two-sided**	**One-sided**	**Two-sided**	**One-sided**
E1	2.474	1.323	6.284	4.225
E2-W1	4.984	17.774	8.085	12.336
E2-W2	8.255	12.341	8.621	6.931
E3	3.431	1.857	8.013	5.532
E4	4.534	2.577	8.885	7.737

Table D2. Results from Bayes factors (BF_{01}).

[1] We used a Cauchy distribution centered on zero with a scale parameter of $\sqrt{2}/2$, i.e., Cauchy (0, 0.707) that has been suggested as a prior for the standardized mean difference in Bayesian t tests (e.g., Camerer et al., 2018; Newell and Le Pelley, 2018). We report both two-sided (H_0: $\delta=0$; H_1: $\delta\neq0$) and one-sided (H_0: $\delta=0$; H_+: $\delta>0$) Bayes factors that take into account the direction of the effect from the original study (e.g., see Wagenmakers et al., 2018). Following Wagenmakers et al., 2018, since the Bayes factor favours H0, we report "BF_{01}" instead of the mathematically equivalent statement "BF_{10}" for ease of interpretation. All calculations were implemented using software JASP (JASP team, 2018).

As a next step, we calculate the original effect size of the Cohn et al. (2015) study and compare whether it lies within the 95% confidence interval estimated from our experiments (Open Science Collaboration, 2015). Table D3 reports effect sizes and 95% CIs across all studies using Cohen's d (Cohen, 1988): the mean difference in risk taking between the positive and negative treatments, divided by the pooled standard deviation. Notably, all of the replication effect sizes are much smaller than the original study effect and all 95% CIs include zero. For the subset of our studies we find that zero out of the five replication CIs contains the original effect size of 0.421 in the risk variant and one out of five replication CIs contains the original effect of 0.275 in the ambiguity variant.

	RISK	**AMBIGUITY**
Study	**Cohen's d (95% CI)**	**Cohen's d (95%CI)**
Cohn et al. (2015)	0.421 (0.108, 0.732)	0.275 (-0.035, 0.584)
E1	0.181 (-0.048, 0.410)	0.078 (-0.151, 0.307)
E2-W1	-0.111 (-0.310, 0.087)	-0.046 (-0.244, 0.152)
E2-W2	-0.043 (-0.239, 0.152)	0.032 (-0.164, 0.227)
E3	0.137 (-0.048, 0.322)	0.057 (-0.128, 0.242)
E4	0.119 (-0.077, 0.315)	0.019 (-0.177, 0.215)

Table D3. Effect size estimates and 95% CI for the risk and ambiguity variants of the tasks.

We finally complement our analysis using prediction intervals (Patil et al., 2016; Spence and Stanley, 2016). For each study, the prediction interval is calculated based on the effect size of the original study and the sample sizes of the original study and each replication attempt to provide a way to assess if the difference between the original and the replication result is consistent with what can be expected due to sample error alone (Patil et al., 2016; Spence and Stanley, 2016); that is, if the replication d-value differs from the original d-value only due to sampling error, there is a 95% chance the replication result will fall in this interval. In this analysis the 95% prediction interval is reported using the approach of Spence and Stanley (2016) that allows calculating of prediction intervals for standardized mean differences.[2] Table D4 reports the results from the replication experiments. Eyeballing Table D4, two things emerge. First, we can see that most of the actual effect sizes reported in Table D3 fall within the prediction intervals of Table D4. Indeed, there are only two cases (the two replications of E2 in the risk variant) that fall outside the prediction interval based on the effect size of the original study. Second, we observe that all the prediction intervals are very wide from negative/close-to-zero values to positive and large values. The width of the prediction intervals depends on the sample size of both the original and the replication studies, and if either of them is small, the prediction interval will be wide and not very informative about replication success (Patil et al., 2016; Spence and Stanley, 2016).[3]

[2] The analysis has been done using the web-based calculator created by Spence and Stanley (2016) available at https://replication.shinyapps.io/dvalue/ (2018, September 27). We use d=0.42 for the original study risk effect size (unrounded d= 0.4205341 and d=0.27 for the original study ambiguity effect size (unrounded d=0.2748002).
[3] If we increase the sample size ten times more than the original study (recruiting 850 for the positive and 770 participants for the negative treatment), the prediction intervals would still not be very informative ((0.09, 0.75) for the risk and (-0.06, 0.59) for the ambiguity variant of the task).

	RISK	AMBIGUITY
Study	**(95% PI)**	**(95% PI)**
E1	(0.03, 0.81)	(-0.12, 0.66)
E2-W1	(0.05, 0.79)	(-0.10, 0.64)
E2-W2	(0.05, 0.79)	(-0.10, 0.64)
E3	(0.06, 0.78)	(-0.09, 0.63)
E4	(0.05, 0.79)	(-0.10, 0.64)

Table D4. Prediction intervals for the replication effect sizes

References

Braver, S. L., Thoemmes, F. J., & Rosenthal, R. (2014). Continuously cumulating meta-analysis and replicability. *Perspectives on Psychological Science*, *9*(3), 333-342.

Camerer, C. F., Dreber, A., Holzmeister, F., Ho, T. H., Huber, J., Johannesson, M., ... & Altmejd, A. (2018). Evaluating the replicability of social science experiments in Nature and Science between 2010 and 2015. *Nature Human Behaviour*, 1.

Cohen, J. (1988). Statistical power analysis for the behavioral sciences (2nd ed.). Hillsdale, NJ: Erlbaum.

JASP Team (2018). JASP (Version 0.9) [Computer software]

Lee, M. D., & Wagenmakers, E. J. (2014). *Bayesian cognitive modeling: A practical course*. Cambridge university press.

Morey, R. D., & Rouder, J. N. (2011). Bayes factor approaches for testing interval null hypotheses. *Psychological methods*, *16*(4), 406.

Newell, B. R., & Le Pelley, M. E. (2018). Perceptual but not complex moral judgments can be biased by exploiting the dynamics of eye-gaze. *Journal of Experimental Psychology: General*, *147*(3), 409.

Newell, B. R., & Shaw, B. (2017). Priming Risky Choice: Do Risk Preferences Need Inferences?. *Journal of Behavioral Decision Making*, *30*(2), 332-346.

Open Science Collaboration. (2015). Estimating the reproducibility of psychological science. *Science*, *349*(6251), aac4716.

Patil, P., Peng, R. D., & Leek, J. T. (2016). What should researchers expect when they replicate studies? A statistical view of replicability in psychological science. *Perspectives on Psychological Science*, *11*(4), 539-544.

Rouder, J. N., Speckman, P. L., Sun, D., Morey, R. D., & Iverson, G. (2009). Bayesian t tests for accepting and rejecting the null hypothesis. *Psychonomic bulletin & review*, *16*(2), 225-237.

Shanks, D. R., Newell, B. R., Lee, E. H., Balakrishnan, D., Ekelund, L., Cenac, Z., ... & Moore, C. (2013). Priming intelligent behavior: An elusive phenomenon. *PloS one*, *8*(4), e56515.

Shanks, D. R., Vadillo, M. A., Riedel, B., Clymo, A., Govind, S., Hickin, N., ... & Puhlmann, L. (2015). Romance, risk, and replication: Can consumer choices and risk-taking be primed by mating motives?. *Journal of Experimental Psychology: General*, *144*(6), e142.

Spence, J. R., & Stanley, D. J. (2016). Prediction Interval: What to Expect When You're Expecting… A Replication. *PloS one*, *11*(9), e0162874.

Wagenmakers, E.-J., Love, J., Marsman, M., Jamil, T., Ly, A., Verhagen, J., et al. (2018). Bayesian statistical inference for psychological science. Part II: Example applications with JASP. *Psychonomic Bulletin & Review, 25*, 48–76.

Wetzels, R., Matzke, D., Lee, M. D., Rouder, J. N., Iverson, G. J., & Wagenmakers, E. J. (2011). Statistical evidence in experimental psychology: An empirical comparison using 855 t tests. *Perspectives on Psychological Science*, *6*(3), 291-298.